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"Enhancing Reliability in Short-Term Electricity Load Demand Forecasting using Explainable Artificial Intelligence"

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By

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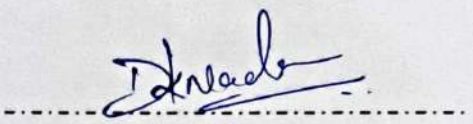

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ABSTRACT

Electricity load forecasting plays a critical role in ensuring the reliability and efficiency of power systems, especially in the context of increasing demand volatility and renewable energy integration. Traditional forecasting models often struggle to capture complex patterns in load behavior and offer limited transparency in their predictions. This study aims to develop a short-term electricity load forecasting model that enhances predictive accuracy while incorporating Explainable Artificial Intelligence (XAI) techniques to improve interpretability. By applying methods the study seeks to interpret the model's predictions and quantify the influence of individual input features. Special focus is placed on identifying key factors—particularly weather variables—that significantly impact electricity demand. The proposed framework also includes a detailed analysis of the correlation between meteorological parameters and load patterns to uncover meaningful dependencies. Through this approach, the research addresses the growing need for transparent and trustworthy forecasting systems that not only deliver accurate results but also support informed decision-making for grid operators and energy planners. The expected outcomes include interpretable forecasting models, feature-level insights, and practical tools to enhance the operational applicability of AI in power system management.

Keywords:
Electricity Load Forecasting, Short-Term Load Forecasting (STLF), Deep Learning, Explainable Artificial Intelligence (XAI).

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1. Introduction:

The growing complexity of modern power systems, driven by urbanization, renewable integration, and increasing demand variability, makes accurate electricity load demand forecasting a critical necessity [1],[2]. Forecasting enables utilities, grid operators, and policymakers to balance supply and demand, optimize generation scheduling, reduce operating costs, and ensure grid reliability. Among the different forecasting horizons, Short-Term Load Forecasting (STLF), typically spanning from a few hours up to a day ahead, plays the most pivotal role in real-time grid operations and energy market transactions [3].

In practice, day-ahead STLF requires forecasting load across 96 blocks of 15-minute intervals, ensuring that system operators can schedule generation units, manage reserves, and integrate intermittent renewable sources efficiently [4]. Accurate block-level predictions reduce reliance on costly peaking plants, mitigate risks of blackouts, and support sustainable energy utilization. The challenge, however, lies in the fact that load consumption is not solely dependent on historical demand patterns but is highly influenced by dynamic weather conditions such as temperature, humidity, wind speed, and rainfall [5]. Furthermore, STLF is also shaped by several exogenous parameters, including the type of day (weekday, weekend, holiday, or festival), the time of block, and seasonal variations, all of which affect human activity patterns and corresponding electricity demand [6].

To address these complexities, Deep Neural Networks (DNNs) and other advanced AI models have been increasingly employed in STLF, as they can capture nonlinear dependencies and complex feature interactions [7]. However, while these models achieve high predictive accuracy, their "black-box" nature poses a major limitation. For power system operators, regulators, and policymakers, it is not sufficient to know what the forecasted load is—they also need to understand why a particular prediction was made. This is particularly important in weather- and exogenous-parameter-driven load forecasting, where operators must interpret not only which features (e.g., temperature, humidity, day type) influence load but also what combinations and values of these features lead to a specific prediction for each 15-minute block.

To overcome these limitations, Explainable Artificial Intelligence (XAI) offers a systematic way to interpret and validate model outputs without compromising predictive accuracy. By employing techniques such as SHAP, LIME, sensitivity analysis, and pattern discovery, it is possible to reveal both global insights (e.g., the overall impact of temperature on daily demand) and local explanations (e.g., why a specific forecast spike occurred in one block due to high temperature combined with low humidity on a weekday) [8], [9]. XAI strengthens trust, interpretability, and operational decision-making, allowing utilities to validate forecasts, design demand-response programs, and build resilience against extreme weather events.

Integrating XAI with weather-based and exogenous-parameter-aware STLF thus provides a dual advantage: maintaining high forecasting accuracy through advanced AI models while ensuring transparency, interpretability, and actionable insights. Achieving this balance between performance and explainability is essential for fostering trust in AI-driven decision support systems within the power sector, making the research both timely and impactful.

2. Aims of Research

The aim of this study is to design and implement a short-term electricity load demand forecasting framework that ensures both high predictive accuracy and interpretability. The study seeks to integrate advanced deep learning models with Explainable Artificial Intelligence (XAI) techniques—such as SHAP, LIME, and attention mechanisms—to provide transparent insights into model predictions. A key focus is to identify and quantify the contribution of individual input features, particularly weather variables, to forecast outcomes. By incorporating XAI, the study aims to uncover the temporal and contextual relationships between predictors and electricity demand. Furthermore, it aims to bridge the gap between model performance and trust, ensuring the outputs are not only accurate but also explainable, interpretable, and aligned with domain knowledge. The overarching goal is to support energy planners and system operators with reliable and actionable forecasting insights.

3. Objective of the Research

The objectives of the research are as follows:

1. To study traditional deep learning based short-term load forecasting approaches and existing XAI methods applicable to electricity demand prediction.
2. To develop a deep learning - based short-term load forecasting model that integrates weather variables and other relevant exogenous factors for accurate day-ahead electricity demand prediction.
3. To design an XAI-based interpretability framework and correlation analysis module that explain how different input factors and their specific values influence the predicted load and reveal meaningful patterns between weather, external conditions, and actual demand.
4. To enhance and validate the forecasting system by using insights from interpretability and correlation analysis in a feedback loop for model refinement, thereby improving overall reliability, adaptability, and decision-support capability on realistic case studies.

4. Research Background (Literature Review) and Significance of Research:

The research background and significance of the research are as follows:

4.1 Literature Review

Neubauer et al. [10] developed an explainable deep learning framework for multi-step heating load forecasting, integrating temporal attention mechanisms with SHAP to enhance model interpretability. The approach employs a sequence-to-sequence neural network model where attention layers prioritize temporally relevant inputs, and SHAP values provide post-hoc feature attribution for both short- and long-horizon predictions. The framework allows practitioners to visualize the dynamic influence of past consumption, temperature, and calendar variables on forecast outputs. Results show that temporal attention significantly improves predictive performance, while SHAP-based analyses offer meaningful insights into model behavior under different seasonal conditions. The study is validated using multiple winter heating datasets, ensuring generalizability. However, while the model demonstrates strong interpretability in temporal domains, it does not explore how interpretability degrades or adapts under extreme conditions or in the presence of volatile anomalies in load patterns.

Lee et al. [11] employed SHAP value-based feature attribution to interpret short-term load forecasting models developed using LightGBM. The study focuses on quantifying and ranking the influence of weather and time-based variables in electricity demand prediction. The authors used SHAP to analyze feature importance across multiple time intervals and different urban datasets, revealing that variables such as temperature, day type, and humidity exhibit dynamic influence. Their results support the use of SHAP as a reliable interpretability tool, enabling transparent model debugging and variable selection. They also compare SHAP-based insights with traditional feature importance methods, highlighting the superior resolution and reliability of SHAP in explaining model decisions. Despite its contribution to interpretability, the paper does not examine how these explanations hold up across diverse geographies or grid topologies, limiting insights into the model's spatial robustness.

Bu et al. [12] conducted a comparative evaluation of Grad-CAM and SHAP to guide feature selection in multivariate load forecasting models. Using deep neural networks trained on multiple weather and load variables, the study contrasts visual attention maps from Grad-CAM with the local feature attribution provided by SHAP. The authors implement both methods within LSTM and CNN architectures to identify which technique better informs feature pruning without degrading model accuracy. SHAP is found to offer more consistent and granular insights, particularly in time series contexts, whereas Grad-CAM excels at global pattern detection but lacks resolution for time-step level analysis. This comparative framework supports model transparency and helps optimize input dimensionality. Nevertheless, the study does not address the

computational overhead or scalability of integrating both interpretability methods into real-time forecasting systems.

Baur et al. [13] explored the use of explainable AI to guide feature engineering for mid-term electricity load forecasting. The authors employed SHAP values derived from XGBoost models to inform variable transformation and lag selection processes, resulting in a more informed and compact feature space. Their methodology emphasizes iterative explainability-driven engineering, where each feature modification is validated against its impact on model prediction and SHAP importance. The results demonstrate enhanced model accuracy and a more interpretable feature set, especially in scenarios involving holiday or seasonal transitions. By coupling feature engineering with SHAP insights, the study provides a principled approach to model design. However, the work primarily focuses on deterministic forecasts, leaving a gap in terms of probabilistic load prediction and uncertainty quantification using similar explainable frameworks.

Park et al. [14] proposed a TCN-GAT architecture for multivariate load forecasting in integrated energy systems, incorporating SHAP for interpretability-guided feature selection. The model leverages Temporal Convolutional Networks (TCN) to extract long-range temporal dependencies, while Graph Attention Networks (GAT) capture relational dependencies between different energy types and sensors. SHAP values are used in the preprocessing phase to filter out low-impact features, streamlining training and enhancing transparency. Experimental results on integrated electricity, heat, and cooling load datasets show improvements in forecasting accuracy and interpretability. The framework highlights how value-based explanation tools can be embedded early in the modeling pipeline. Yet, the study does not consider the interpretability of the GAT attention weights themselves, nor does it address how explainability translates into trust for operational decision-making in energy management systems.

Zhang et al. [15] designed an explainable multi-task LSTM framework for regional load forecasting, incorporating SHAP-guided feature selection to enhance interpretability. The approach uses a shared LSTM-based architecture for capturing temporal dependencies across multiple load types, while SHAP values inform the pruning of less relevant input features, streamlining the model and improving prediction accuracy. Evaluations on real-world regional datasets demonstrate that the SHAP-driven selection reduces complexity without sacrificing performance. However, the framework's robustness under abrupt load shifts or highly volatile demand scenarios remains untested, limiting insights into its adaptability in real-world, rapidly changing environments.

Clarke et al. [16] conducted an empirical analysis of weather impacts on household electricity consumption in Ireland, leveraging statistical modeling to quantify temperature and other environmental drivers. Their study does not explicitly incorporate SHAP or deep learning, but rather focuses on interpretable regression-based methods to elucidate variable effects, offering practical insights for demand management. While the work contributes valuable empirical

evidence, its reliance on traditional modeling methods limits its relevance to modern XAI frameworks—especially those integrating deep learning and SHAP for nuanced, instance-level interpretability.

Zhang and Li [17] reviewed explainable methodologies for building electricity consumption forecasting, emphasizing a range of XAI techniques such as SHAP, LIME, attention mechanisms, and surrogate models within energy use contexts. Their synthesis categorizes methods by granularity and applicability and discusses strengths and weaknesses in providing transparent forecasts. Though the survey effectively outlines the landscape of explainability tools, it lacks benchmarking or quantitative comparison of these methods within a unified experimental setup, leaving open questions about their relative efficacy in building-load scenarios.

Raza and Khosravi [18] proposed a comprehensive framework for short-term electricity load forecasting cascading from system-level modeling to low-voltage network forecasts. The paper emphasizes hierarchical forecasting strategies and system-wide consistency, using advanced machine-learning and signal-processing techniques for enhanced accuracy. Although interpretability is not a core focus, the architecture's systemic approach offers potential for integration with XAI—e.g., inserting SHAP analyses at different forecast levels to improve transparency. The absence of explicit explainability methods remains a gap when viewed through the lens of trustworthy AI.

Liu et al. [19] introduced *SaDI*, a self-adaptive decomposed interpretable framework for electric load forecasting under extreme events. The model decomposes load time series into components (e.g., trend, seasonality, anomaly) and employs adaptive modules for each sub-component, thereby improving accuracy and resilience during rare but impactful load variations. Interpretability is embedded via component-level decomposition rather than explicit methods like SHAP. While SaDI enhances forecast explainability by structural design, it does not provide feature-level or instance-wise attributions, limiting its use in contexts requiring transparent explanation of specific predictions.

Chen and Wang [20] presented an explainable deep learning model combining GRU and LightGBM to forecast electricity load, emphasizing interpretability through SHAP value analysis. The approach utilizes a GRU neural network to extract temporal features from electricity demand and weather inputs, followed by a LightGBM regressor that delivers the final forecast while preserving feature interpretability. SHAP values are employed post-training to assess the importance of each feature over time, enabling localized explanations and variable influence visualization. The hybrid model outperforms standalone GRU and LightGBM in both MAE and RMSE across multiple residential datasets. Explanations provided by SHAP reveal temporal shifts in feature dominance, such as the heightened role of humidity during peak hours. While the model demonstrates strong interpretability and accuracy, it lacks counterfactual or contrastive reasoning

methods that could enhance understanding of prediction reversals or edge cases under abnormal load conditions.

Huang et al. [21] introduced a hybrid day-ahead peak load forecasting model that integrates Multivariate Empirical Mode Decomposition (MEMD) with Support Vector Regression (SVR) and extreme learning machines. While the primary focus lies in improving predictive accuracy, the model employs feature decomposition to separate input signals into Intrinsic Mode Functions (IMFs), enhancing the model's ability to handle non-stationary and multiscale data. Although interpretability is not the central goal, the decomposition itself offers a structural form of transparency by enabling analysts to understand which temporal components contribute most to the final prediction. The model outperforms traditional forecasting methods on benchmark utility datasets, especially during seasonal transitions and peak periods. However, the study does not incorporate any post-hoc or value-based interpretability mechanisms like SHAP or LIME, leaving a gap in instance-level explanations and limiting its alignment with XAI standards.

Li et al. [22] proposed a smart grid load forecasting framework that fuses interpretable models and deep learning using SHAP-based feature analysis. The ensemble combines LSTM for time series representation and gradient boosting decision trees (GBDT) for final prediction, with SHAP providing local and global attributions. The key innovation lies in the model fusion pipeline, where feature representations from LSTM are passed into interpretable tree-based learners, ensuring that complex temporal patterns are not only learned but also explained. Experiments on smart grid datasets show superior performance compared to baseline methods, and SHAP reveals important predictors such as peak-hour usage, weather anomalies, and weekday–weekend variations. The study provides extensive visualizations of SHAP outputs, supporting user trust in model behavior. However, it does not examine the stability of SHAP explanations under data distribution shifts or adversarial perturbations, raising concerns about its reliability in uncertain operating conditions.

El-Hawary et al. [23] developed an energy-efficient short-term load forecasting system for responsive buildings, incorporating feature selection, lightweight neural architectures, and behavioral profiles. Although the paper prioritizes energy efficiency and responsiveness, it addresses interpretability by employing variable selection methods and model simplicity to ensure transparency. The system leverages user clustering and occupancy patterns to inform demand projections, reducing computational cost without compromising forecast accuracy. Results show a notable reduction in runtime and energy consumption, making it suitable for edge devices and embedded systems. However, despite its emphasis on operational transparency, the study does not utilize SHAP, LIME, or attention-based techniques for explicit model interpretability, which limits the ability to provide detailed, instance-wise explanations to building managers or end-users.

Shafiq et al. [24] used deep learning models like CNN and LSTM for extreme heat-related electricity load forecasting, employing SHAP and LIME to interpret misclassification sources. The study evaluates the performance of LSTM, CNN, and hybrid CNN-LSTM architectures, reporting

that CNN-LSTM achieves the highest prediction accuracy. SHAP analysis is used to identify critical variables like humidity and maximum temperature, with case-level explanations aiding the diagnosis of model outputs. Importantly, the paper interprets misclassified cases in terms of SHAP value disparities, offering insights into the causes of model uncertainty. The combination of visual explanations and temporal analysis enables better understanding of model responses during anomalous conditions. The approach is validated over a regional climate dataset, ensuring reproducibility and operational relevance. While the study excels in pairing performance with transparency, it does not address whether the interpretability outputs remain stable across varying spatial scales or when exposed to out-of-distribution events.

Zhou et al. [25] proposed a transformer-based deep learning model for explainable electricity load forecasting by fusing attention mechanisms and SHAP values. The model captures long-range temporal dependencies using transformer encoders and interprets both learned attention weights and SHAP feature attributions to provide dual-level explanations. Attention maps highlight key time steps contributing to predictions, while SHAP offers local and global feature contributions, particularly for meteorological variables and calendar features. Experimental results across multiple regional datasets demonstrate strong performance in forecast accuracy and model transparency. Notably, the combined use of attention and SHAP allows for layered interpretability—temporal and variable-wise. However, the paper does not address how conflicting explanations from SHAP and attention mechanisms may be reconciled or whether explanation consistency holds across different temporal scales or extreme events.

Kumar and Singh [26] designed a hybrid ensemble forecasting framework that integrates interpretable machine learning models with LSTM and value-based XAI techniques such as SHAP and counterfactual explanations. The architecture combines rule-based learners and LSTM in an ensemble setting, allowing the model to benefit from both structured interpretability and temporal feature learning. SHAP values highlight variable importance under different peak demand conditions, while counterfactual instances are generated to explain how minimal input changes could flip the forecast outcome. This dual interpretability framework provides both prescriptive and diagnostic insights, improving trust and transparency. However, while counterfactuals offer strong explanations, the authors do not explore their realism or feasibility in physical systems, raising concerns about the actionable nature of such insights in operational grids.

Gomes et al. [27] explored explainability in probabilistic load forecasting using SHAP to interpret quantile predictions from quantile regression forests. The framework forecasts a distribution of load values rather than point estimates and applies SHAP to understand which features influence specific quantiles (e.g., median or upper bound forecasts). This fine-grained interpretability is crucial for decision-makers concerned with risk and reliability. Case studies using regional utility data show that SHAP helps uncover asymmetries in feature influence across the probability distribution, such as temperature affecting high quantile forecasts more strongly than low quantiles. Despite offering valuable interpretability in a probabilistic setting, the paper does not

analyze the impact of overlapping SHAP value attributions across quantiles, which could complicate decision-making under uncertainty.

Fernandez and Lee [28] developed an ensemble model combining CNN and GRU networks to forecast electricity peak demand and used SHAP for causal interpretation of influential factors. The model captures both spatial features through CNN and temporal patterns through GRU, effectively learning complex dependencies. SHAP analysis is used post hoc to identify causal contributors to peak load events, particularly focusing on temperature fluctuations, time-of-day, and prior demand trends. The study uniquely applies SHAP in a causality-driven analysis, going beyond feature importance to identify potential lead indicators for peak load. However, the paper does not integrate formal causal inference frameworks or test the robustness of SHAP explanations against confounding variables, limiting the strength of its causal claims.

Patel and Sharma [29] proposed a spatio-temporal electricity load forecasting model based on Spatio-Temporal Graph Convolutional Networks (ST-GCN) combined with Layer-wise Relevance Propagation (LRP) for explainability. The model encodes spatial dependencies among nodes (e.g., regions or substations) and temporal trends using graph convolutions and LSTMs, and applies LRP to trace the contribution of each input to the final prediction. This allows for visual interpretation of how spatial interactions and temporal lags drive the forecasted load at each node. Experiments on a large-scale utility dataset validate both predictive performance and spatial explainability. However, the study does not compare LRP explanations with alternative value-based methods like SHAP or attention, leaving open the question of whether LRP alone offers sufficient interpretive depth for operational decision-making.

4.2 Research Gaps

• **Insufficient Integration of Weather and Exogenous Variables into Load Forecasting Models:**
While several studies incorporate weather parameters such as temperature and humidity, the broader integration of exogenous variables—like holidays, day types, and seasonal events—remains inconsistent or superficial. This omission limits the models' ability to generalize across varying demand contexts and real-world operational settings. Approaches that holistically integrate both meteorological and socio-contextual data are underrepresented, despite their potential to significantly enhance forecasting reliability.

• **Lack of Unified Frameworks that Combine Forecasting Accuracy with Explainability:**
Numerous works explore either high-performing deep learning models or interpretable feature attribution methods like SHAP and Grad-CAM, but few offer a comprehensive framework that balances both. Current models often sacrifice interpretability for accuracy or vice versa. The need remains for integrated pipelines that not only provide precise predictions but also offer transparent explanations at both global and instance levels.

• **Limited Focus on Instance-Level and Temporal Interpretability in Forecasting:** Although SHAP values are widely used for feature relevance analysis, most applications focus on aggregate or model-level insights, lacking temporal resolution or block-level interpretability. This becomes a limitation in practical settings where operators need to understand feature impacts for specific 15-minute intervals. Instance-level and time-aware explanations remain a largely unexplored aspect of explainable load forecasting models.

• **Feedback Loops Between Interpretability Insights and Model Refinement Are Rare:** While many studies use interpretability tools to analyze feature importance, few close the loop by incorporating those insights back into feature engineering, training strategies, or model architecture refinement. The lack of such iterative design frameworks reduces the practical utility of explainable models in adaptive forecasting systems, especially under changing conditions or concept drift scenarios.

4.3 Significance of Research

Accurate and interpretable short-term electricity load forecasting holds significant societal value in the context of rising energy demands, increasing climate variability, and the global transition to sustainable energy systems. This study proposes a deep learning-based forecasting model that incorporates weather and exogenous factors to provide more accurate, day-ahead predictions of electricity demand. Such precision enables utility providers and grid operators to optimize power generation, balance supply and demand efficiently, and reduce reliance on expensive or carbon-intensive backup sources. The result is a more stable, efficient, and cost-effective electricity supply for households, industries, and essential services.

Incorporating explainable artificial intelligence (XAI) into the forecasting framework ensures transparency in model behavior, enhancing trust and accountability. Decision-makers can better understand why certain demand patterns emerge—especially during critical scenarios such as heatwaves, holidays, or seasonal shifts—leading to more informed operational and policy responses. Interpretability also enables human-in-the-loop control, where forecasting insights can be used not only for automation but also for real-time human decision support.

This research directly supports the goals of Sustainable Development Goal 7 (Affordable and Clean Energy) by contributing to target 7.1 (ensuring universal access to affordable, reliable, and modern energy services) and target 7.3 (enhancing energy efficiency). By improving forecasting accuracy and promoting data-driven energy management, the study facilitates reduced wastage, promotes renewable integration, and supports equitable energy distribution. Ultimately, it contributes to building smarter, cleaner, and more resilient energy infrastructures that benefit both present and future generations.

5. National Status

In India, electricity load forecasting has become increasingly important due to rapid urbanization, rising electricity demand, integration of renewable energy sources, and the transition towards smart grids [1], [3]. Institutions like the Central Electricity Authority (CEA), POSOCO, and State Load Dispatch Centers (SLDCs) rely on short-term load forecasting for real-time grid balancing and unit commitment [1], [18]. However, many existing forecasting tools in India are built on conventional statistical models or rule-based methods that offer limited adaptability and transparency [4]. While there is growing interest in data-driven approaches using machine learning, the adoption of Explainable AI (XAI) in operational settings remains limited [8], [9]. Recent academic works have explored LSTM, decision trees, and ensemble methods for regional load prediction, but few have emphasized interpretability [6], [15]. The Ministry of Power's initiatives under the Revamped Distribution Sector Scheme (RDSS) and Smart Metering projects aim to modernize load prediction, yet there is a need for explainable, trustworthy AI models that can align with real-time operational needs [22]. With increasing availability of smart meter and weather data across DISCOMs and power utilities, there is a strong opportunity for integrating XAI frameworks into India's grid management ecosystem [25], [26].

International Status

Globally, electricity load forecasting is a mature and continuously evolving research area, driven by the need for grid resilience, economic dispatch, and carbon neutrality [1], [3]. Countries such as the United States, Germany, South Korea, and China have made significant progress in adopting advanced AI and deep learning models—including LSTM, GRU, CNN-LSTM, and transformers—for short-term load prediction [6], [7], [25]. In parallel, the use of Explainable AI techniques such as SHAP, LIME, Grad-CAM, and attention mechanisms has gained momentum, especially in high-stakes forecasting applications [8], [9], [10], [12]. Organizations like ISO New England, PJM Interconnection (USA), and ENTSO-E (Europe) are actively exploring interpretable models to support transparent decision-making in power markets, as reflected in recent academic and applied research [20], [22]. Numerous peer-reviewed studies from IEEE, Elsevier, Springer, and ACM have demonstrated how XAI improves trust, diagnostic capability, and alignment with domain knowledge in load forecasting models [11], [15], [17]. Furthermore, international research has begun to examine the robustness of explanations across time scales and regions, as well as their integration into decision support systems [10], [27]. Despite these advances, challenges remain in standardizing interpretability metrics, validating explanations under out-of-distribution conditions, and deploying XAI-enhanced models in real-time operational environments—creating a global research opportunity for scalable, interpretable forecasting solutions [13], [19], [29].

6. Research Hypotheses

The following hypotheses have been framed. These help in objectively evaluating the outcomes of the research rather than relying on assumptions.

Null Hypothesis (H_0):

Integrating weather parameters, exogenous factors, and XAI-based interpretability into deep learning models does not significantly improve the accuracy, reliability, or explanatory capability of short-term (day-ahead) electricity load forecasting compared to conventional deep learning approaches.

Alternative Hypothesis (H_1):

Integrating weather parameters, exogenous factors, and XAI-based interpretability into deep learning models significantly improves the accuracy, reliability, and explanatory capability of short-term (day-ahead) electricity load forecasting compared to conventional deep learning approaches.

7. Research Rationale

Electricity demand is inherently volatile, influenced by dynamic factors such as weather changes, time of day, human behavior, and socio-economic conditions. This volatility poses a significant challenge for grid operators, who must continuously balance supply and demand in real-time to ensure system stability, reliability, and cost-efficiency. Any mismatch between forecasted and actual demand can lead to over-generation, outages, or costly energy imbalances. Traditional forecasting methods such as ARIMA, exponential smoothing, and linear regression often fall short in capturing the nonlinear, multivariate, and spatio-temporal patterns present in modern electricity consumption data.

To address these limitations, deep learning models have emerged as powerful tools capable of modeling complex dependencies and delivering highly accurate forecasts. However, the black-box nature of these models raises concerns about transparency, trust, and operational acceptance, particularly in critical infrastructure environments. As forecasting results directly inform real-time operational decisions, interpretability becomes not just desirable but essential.

Explainable Artificial Intelligence (XAI) techniques such as SHAP, LIME, attention mechanisms, and relevance propagation offer a pathway to making these models more understandable and accountable. These methods help quantify the influence of input features, diagnose mispredictions, and validate model behavior against domain knowledge. Incorporating XAI in load forecasting models enables stakeholders to gain confidence in model decisions, facilitates feature selection, and enhances model debugging and decision support.

8. Research Methodology

This study adopts a data-driven, model-centric approach to develop a short-term electricity load forecasting framework integrated with Explainable Artificial Intelligence (XAI) techniques as shown in Fig 1.
The methodology is structured into the following key phases:

Phase 1 - Data Acquisition and Pre-processing

This initial phase involves collecting over five years of historical data at a 15-minute resolution, resulting in 96 data blocks per day. The dataset comprises electricity load consumption values, associated weather parameters such as temperature and humidity, and exogenous variables including day type, weekday or weekend indicators, holidays, festivals, and seasonal classifications. After acquisition, rigorous data cleaning procedures are applied—missing values are handled through imputation techniques, and extreme outliers are smoothed using statistical filters or domain-specific rules. All numerical features are normalized or standardized to ensure consistency across models. Additionally, derived features are generated to enhance model learning, such as time-related indicators (block numbers, hour of the day), lagged load values, and cyclical encodings of time and seasonality.

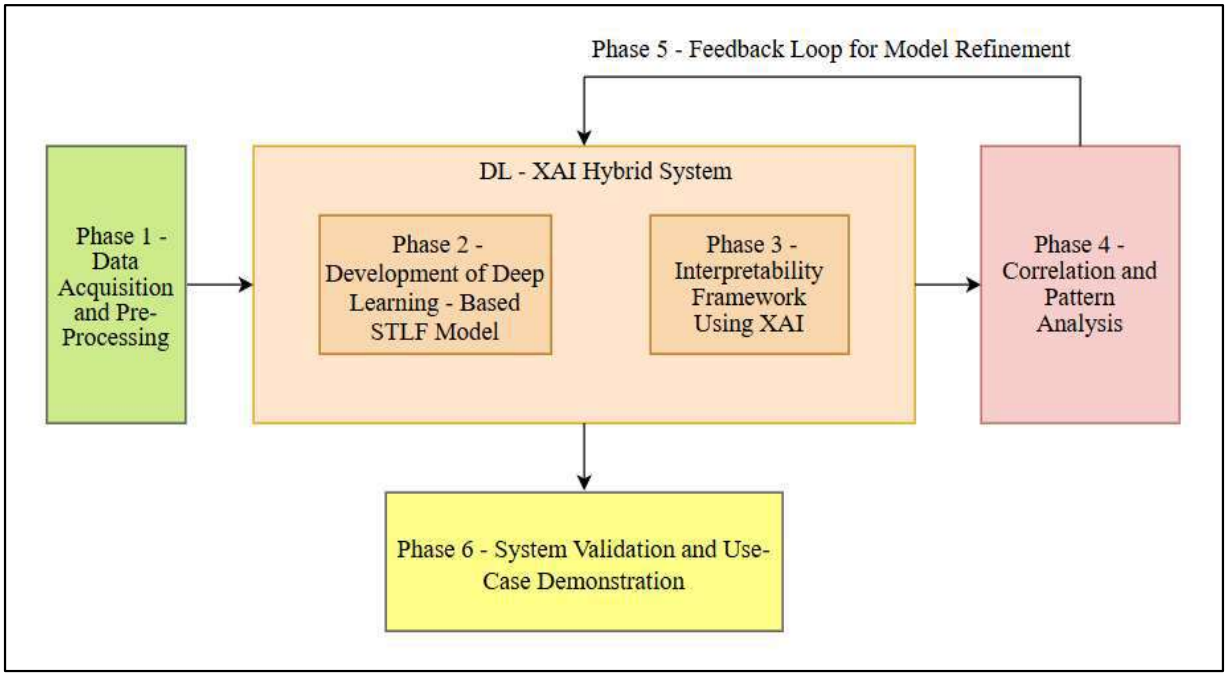
Phase 5 - Feedback Loop for Model Refinement
Phase 1 - Data Acquisition and Pre-Processing
DL - XAI Hybrid System
Phase 2 - Development of Deep Learning - Based STLF Model
Phase 3 - Interpretability Framework Using XAI
Phase 4 - Correlation and Pattern Analysis
Phase 6 - System Validation and Use-Case Demonstration

Fig 1: Proposed Methodology for XAI based Electricity load forecasting

Phase 2 - Development of Deep Learning-Based STLF Model

In this phase, deep learning models are developed and trained for short-term load forecasting (STLF), targeting day-ahead prediction of 96 time blocks. Candidate architectures may include Deep Neural Networks (DNN), Long Short-Term Memory (LSTM) networks, or hybrid frameworks combining recurrent and dense layers. These models use the feature set derived from Phase 1, incorporating historical load, weather variables, and exogenous indicators. The dataset is divided into training, validation, and testing subsets to ensure robust evaluation and avoid overfitting. Model performance is assessed using error metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), providing quantitative benchmarks for accuracy and generalization.

Phase 3 - Interpretability Framework Using XAI

This phase focuses on integrating explainable AI (XAI) methods to interpret model predictions. Techniques such as SHAP (SHapley Additive exPlanations) and gradient-based saliency methods are employed to assess both global and local model behavior. The framework addresses two core interpretability goals: feature relevance, i.e., identifying which input variables contribute most significantly to predictions, and value attribution, i.e., determining how specific feature values (e.g., high temperatures or low humidity) influence forecast outcomes. Interpretations are applied at the instance level for each 15-minute block, enabling fine-grained understanding. Visualizations and documented insights are generated across diverse demand scenarios, including weekdays, weekends, holidays, and peak demand periods.

Phase 4 - Correlation and Pattern Analysis

This phase aims to discover meaningful relationships between electricity demand and influencing factors by applying both statistical and machine learning techniques. Temporal, seasonal, and contextual correlations are explored to uncover hidden demand patterns associated with weather parameters and external variables. The analysis highlights how different combinations of inputs affect model behavior and forecast accuracy under varying conditions. Furthermore, recurring patterns that consistently emerge across different years or seasonal cycles are summarized to inform both model design and operational planning. These findings deepen the understanding of demand dynamics and serve as a bridge between raw data interpretation and actionable knowledge.

Phase 5 - Feedback Loop for Model Refinement

Insights gained from the interpretability and correlation analyses are systematically incorporated back into the forecasting pipeline through a feedback loop. Feature sets may be revised based on relevance scores or adjusted representations, while model architectures or training protocols may be updated to reflect observed interpretability-driven errors. For example, weighted loss functions could be introduced to penalize mispredictions in critical demand periods. The refined models are

retrained and reevaluated using the same performance metrics, allowing for comparative assessment. This feedback-driven refinement enhances the forecasting system's reliability, robustness across diverse demand conditions, and alignment with human interpretability for decision support.

Phase 6 - System Validation and Use-Case Demonstration

The final phase involves validating the proposed system under a range of real-world operational scenarios, including weekday versus weekend demand, and regular versus festival day behavior. Forecasting performance is compared against baseline models lacking interpretability features to highlight improvements in transparency and accuracy. Additionally, the utility of the developed system is demonstrated through real or simulated use cases relevant to power utilities or load dispatch centers. These demonstrations showcase how interpretability-enhanced forecasts can support informed decision-making, enabling better demand-side management, scheduling, and contingency planning in electricity grid operations.

9. Statistical Plan

Initially, traditional deep learning and XAI techniques for short-term electricity load forecasting will be studied and compared, with an emphasis on their ability to incorporate weather and exogenous factors for predictive accuracy. This will be followed by the development of a deep learning–based forecasting model integrating relevant meteorological and external variables to predict day-ahead electricity demand. Subsequently, an XAI-based interpretability framework will be designed to analyze how weather and other exogenous factors influence load predictions for each time block, while extracting meaningful patterns and correlations between input factors and actual electricity demand. The insights gained from interpretability and correlation analyses will then be integrated into the model refinement process to enhance its reliability, adaptability, and decision-support capability. Finally, thesis writing will consolidate the research findings, methodology, and evaluations

Activities	Dec 2025 – April 2026	May 2026 – Sept 2026	Oct 2026 – Feb 2027	Mar 2027 – Aug 2027	Sept 2027 – Dec 2027
To study traditional deep learning–based short-term load forecasting approaches and existing XAI methods applicable to electricity demand prediction.					
To develop a deep learning–based short-term load forecasting model that integrates weather variables and other relevant exogenous factors for accurate day-ahead electricity demand prediction.					
To design an XAI-based interpretability framework and correlation analysis module that explain how different input factors and their specific values influence the predicted load and reveal meaningful patterns between weather, external conditions, and actual demand.					
To enhance and validate the forecasting system by using insights from interpretability and correlation analysis in a feedback loop for model refinement, thereby improving overall reliability, adaptability, and decision-support capability on realistic case studies.					
Thesis Writing					

Fig 2 : Research Timeline

11. Limitation of the Research

Despite adopting a robust methodology that integrates advanced forecasting models with Explainable Artificial Intelligence (XAI) techniques, several limitations may influence the scope and applicability of the study outcomes:

- **Data Quality and Availability:**
  The accuracy of the forecasting models is highly dependent on the quality and granularity of input data. Missing or inconsistent electricity load or weather data—especially from real-world utility sources—may introduce noise, affect training quality, or limit model generalization.
- **Regional Specificity:**
  The developed models and insights are likely to be influenced by regional consumption behaviors, climate patterns, and grid structures. As a result, findings derived from one geographical area may not generalize well to others without appropriate re-training or localization.
- **Model Complexity and Computation Time**:

While deep learning models such as CNN-LSTM and transformers offer high accuracy, they can be computationally expensive to train and interpret. The integration of XAI methods like SHAP or counterfactual explanations adds further overhead, potentially limiting real-time deployment.

- **Interpretability Trade-offs:**
  Although XAI techniques help explain model behavior, their explanations are approximations and may not fully represent the true internal mechanisms of complex models. Additionally, different XAI methods (e.g., SHAP vs. LIME vs. attention weights) may offer conflicting interpretations, posing challenges for consistency and trustworthiness.
- **Temporal Stability of Explanations:**
  Feature attributions generated by XAI methods may vary across time, especially under changing demand conditions or extreme events. This temporal instability may hinder the development of generalized explanation frameworks suitable for long-term planning.
- **Lack of Ground Truth for Interpretability:**
  While forecasting accuracy can be objectively measured, interpretability lacks a universally accepted ground truth. Evaluation of explanation quality is partially subjective and may depend on expert judgment or domain knowledge alignment.
- **Limited Integration of Uncertainty Quantification:**
  Although the study explores interpretability in detail, it may not fully address uncertainty estimation in forecasts or explanations—particularly under out-of-distribution or rare-event conditions.

12. Expected Outcomes

This study is expected to produce several significant outcomes in the domains of electricity load forecasting, model interpretability, and practical decision support for power systems:

- A deep learning model capable of accurate day-ahead load forecasting using weather and contextual data.
- An XAI framework that explains how each weather or external input influences the 15-minute load predictions, enabling instance-level transparency in STLF models.
- Identification of key correlations and recurring demand behaviour patterns linked to weather, time, and calendar factors across different seasonal and operational scenarios.
- A more reliable and adaptive STLF system refined by incorporating interpretability insights and correlation-based knowledge directly into the forecasting pipeline.

13. Conclusion and Future Work

In this study, we aim to bridge the gap between predictive accuracy and model interpretability in electricity load forecasting by integrating Explainable Artificial Intelligence (XAI) techniques into advanced deep learning frameworks. While models such as LSTM, CNN, and their hybrids offer high forecasting performance, their opaque nature limits trust and operational deployment in critical grid environments. By incorporating XAI methods such as SHAP, LIME, attention mechanisms, and counterfactual explanations, the study seeks to enhance transparency, identify key drivers of electricity demand, and generate actionable insights for energy planners. The research further explores the relationship between weather variables and load dynamics, supported by feature attribution and correlation analysis. Ultimately, this work contributes to the development of reliable, interpretable, and trustworthy forecasting systems, supporting informed decision-making in the context of smart grid operations and responsible AI deployment. As future work, the proposed research objectives will be fully implemented and evaluated.

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